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A Global Interaction–Inspired Metaheuristic for Neural Network Optimization in Geological Modeling by the World Algorithm

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Abstract

The growing complexity of geological modeling demands intelligent optimization strategies capable of handling nonlinear, multi-modal, and data-scarce environments. This study introduces World, a novel global interaction–inspired metaheuristic algorithm designed for neural network optimization in geoscientific applications. Rooted in the ecological dynamics of interdependent entities, the World algorithm integrates adaptive learning, social influence mechanisms, and environmental feedback loops to achieve a dynamic balance between exploration and exploitation. The proposed framework was implemented within an Automated Deep Learning (AutoDL) environment (Auto-Keras) and evaluated across three key geoscientific prediction tasks: lithology classification, shear wave velocity estimation, and Total Organic Carbon (TOC) quantification. Two benchmark datasets, from the North Sea and Horn River Basin, were utilized to ensure geological diversity. Comparative analysis against established optimizers, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Bayesian Optimization (BO), and Tree-structured Parzen Estimator (TPE), demonstrated that world consistently achieved faster convergence, higher accuracy, and superior generalization capability. Empirical results revealed an average 12–18% improvement in predictive performance and a 30% reduction in training time, confirming the algorithm's robustness and computational efficiency. Moreover, its dynamic adaptation strategy significantly mitigated the risk of premature convergence commonly observed in traditional metaheuristics.

Keywords: World algorithm, Metaheuristic optimization, Neural network Optimization, Geological modeling, Automated machine learning.

1 | Introduction

The geosciences domain is currently experiencing a technological paradigm shift, largely driven by advancements in Artificial Intelligence (AI). Machine Learning (ML) and Deep Learning (DL) methodologies have emerged as transformative tools, enabling researchers to decode complex geological patterns from

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multidimensional datasets that traditionally resisted conventional analytical approaches. These capabilities have proven particularly valuable in critical tasks, including lithological classification, shear wave velocity modeling, Total Organic Carbon (TOC) quantification, and comprehensive reservoir characterization [1].

Despite these promising developments, significant implementation barriers persist. Conventional ML/DL frameworks demand extensive manual intervention in hyperparameter configuration and architectural design, a process that consumes substantial computational resources and requires specialized expertise not commonly available across geoscientific teams. The challenges are further compounded by inherent limitations, including premature convergence to suboptimal solutions, limited generalization capacity across geological formations, and heightened sensitivity to data quality issues. These constraints become particularly problematic when dealing with sparse well log data or imbalanced datasets from frontier exploration areas, often resulting in unreliable predictions in geologically complex environments [2].

The generalization challenge presents another critical obstacle, as models trained on specific depositional systems frequently fail to maintain accuracy when applied to new geological settings with distinct characteristics. This transfer learning deficit substantially hinders the scalable deployment of AI solutions across diverse exploration projects. Moreover, the opaque decision-making processes characteristic of many deep neural networks create interpretability concerns for geoscientists who require transparent reasoning for critical resource assessment decisions [3].

Addressing these multifaceted challenges requires innovative approaches that combine automation with domain-aware optimization. The emerging fields of Automated Machine Learning (AutoML) and Automated Deep Learning (AutoDL) offer promising pathways by streamlining the end-to-end model development pipeline. These frameworks significantly reduce manual configuration overhead while making sophisticated modeling capabilities accessible to non-specialists. The integration of geological principles and physical constraints directly into the learning architecture represents a significant advancement, bridging the gap between purely data-driven approaches and domain expertise [4].

Within this automated paradigm, Hyper-Heuristic optimization frameworks have demonstrated remarkable capabilities in intelligently orchestrating multiple meta-heuristics. Operating at a higher abstraction level than conventional optimizers, these algorithms dynamically adapt their search strategies according to problem characteristics and optimization progress. The World Hyper-Heuristic algorithm implemented in this study exemplifies this approach through its reinforcement learning foundation, which continuously balances exploration of new solutions with exploitation of known promising regions. This adaptive capability proves especially valuable in geoscientific applications characterized by complex, multi-modal search landscapes [4]. This research systematically investigates the World algorithm's efficacy across three fundamental geoscientific tasks: lithology identification, shear wave velocity prediction, and TOC assessment. These applications represent critical components in reservoir evaluation and petroleum system analysis. Our methodology employs two distinct datasets from North Sea hydrocarbon provinces and the Horn River Basin, ensuring robust evaluation across different geological contexts. Implementation leverages the Auto-Keras framework with comprehensive search spaces encompassing architectural elements, learning parameters, activation functions, and regularization techniques. Rigorous validation protocols ensure reliable performance assessment across varied geological scenarios.

The study's significance extends beyond introducing an advanced optimization methodology to the geoscientific community. By demonstrating the synergistic potential of Hyper-Heuristic optimization within AutoDL frameworks, we provide a scalable template for addressing diverse geoscientific challenges. The practical implications include accelerated resource discovery, reduced exploration uncertainty, and enhanced recovery efficiency through improved subsurface characterization. Furthermore, the established methodology creates foundations for developing increasingly sophisticated automated interpretation systems capable of continuous improvement through incremental learning from new data sources.

This research contributes to the ongoing democratization of AI in geosciences, empowering professionals across experience levels to leverage cutting-edge analytical capabilities while addressing persistent challenges in model transparency, generalization capacity, and implementation efficiency. The findings establish meaningful progress toward next-generation geoscientific workflows that intelligently integrate physical knowledge with data-driven insights through automated, adaptive computational frameworks [5].

2 | Related Work

2.1 | Evolution of Artificial Intelligence in Geosciences

The integration of AI with geosciences narrates a story of dynamic convergence between technology and specialized knowledge. At the dawn of this collaboration, early systems operating on predefined rules entered the realm of geological data interpretation. Although these pioneering systems faced numerous limitations, they opened new horizons for using computational intelligence to analyze the most complex geological problems [6].

Moving into the 1990s, a new generation of intelligent systems based on Artificial Neural Networks (ANNs) emerged. These computational architectures, inspired by the human brain structure, demonstrated remarkable ability in identifying complex patterns within well log data and opened a window toward modeling subsurface heterogeneities [1], [4], [6].

On the threshold of the third millennium, the third generation of intelligent technologies, including Support Vector Machines (SVMs) and ensemble learning methods, swept across the field. These advanced architectures, utilizing complex mathematical concepts, demonstrated unprecedented capability in analyzing multidimensional data and identifying nonlinear relationships [5].

In recent years, the DL revolution has also permeated geosciences. Convolutional Neural Networks, inspired by the human visual cortex, have gained the ability to intelligently extract meaningful features from seismic data, while advanced recurrent architectures have enabled complex temporal analyses [7].

Today, the newly emerging generation of intelligent systems follows an integrated approach combining advanced data mining with fundamental physical laws. These fourth-generation systems not only learn from data but also incorporate the fundamental concepts governing geological phenomena within their architecture [8].

Furthermore, the necessity for transparency in AI decision-making has led to the development of interpretable technologies. These technologies enable geoscience specialists to understand the logic behind intelligent system predictions and utilize them with greater confidence [9].

The future outlook envisions the development of distributed intelligent systems that can learn collaboratively while maintaining data privacy. This transformation, along with the automation of intelligent model development processes, will create a revolution in the speed and quality of geological analyses.

This dynamic evolutionary path has not only transformed the accuracy and efficiency of geological analyses but has also provided new foundations for understanding Earth's most complex mysteries [10].

2.2 | Development of Lithology Prediction Methods

The process of lithology prediction has undergone a significant transformation over time. Initially, geologists used simple mathematical relationships and empirical charts for lithology identification. While these methods were understandable, they faced limitations when dealing with complex geological formations.

With technological advancements, methods based on classical statistics, such as discriminant analysis and linear regression, have replaced traditional approaches. These techniques enabled quantitative classification of rocks but were unable to model nonlinear relationships present in well log data [10–12].

Subsequently, decision tree algorithms and SVMs emerged. These methods, with their capability to identify more complex patterns, enhanced prediction accuracy. However, they still had limitations in extracting relevant features from multidimensional data.

The introduction of ANNs marked a turning point in this field. These networks demonstrated greater flexibility in lithology prediction through their ability to learn complex nonlinear relationships. However, the real progress came with the emergence of DL architectures [2], [4–6].

Convolutional Neural Networks, with their capability to automatically extract spatial features from well log data, created a fundamental transformation in identifying lithological patterns. Simultaneously, Recurrent Neural Networks, with their ability to analyze time sequences, enabled modeling of vertical variations in rocks [9].

In recent years, combining these architectures in the form of hybrid models has yielded significant results. Furthermore, integrating well log data with seismic information within multimodal learning frameworks has provided a more comprehensive understanding of lithological systems.

The development of interpretable methods alongside improved model accuracy has enabled verification and validation of results by expert geologists. These advances have increased trust in AI predictions and expanded their practical application in exploration projects.

Today, research focuses on developing models that can train with limited data and incorporate existing geological knowledge into the learning process. These approaches pave the way for AI applications in data-scarce regions [9], [11], [12].

2.3 | Evolution in Shear Wave Velocity Estimation

The estimation of shear wave velocity (Vs) has progressed through several distinct phases, each marked by increasing methodological sophistication. Initially, the industry relied heavily on simplistic empirical relationships that linked Vs directly to compressional wave velocity (Vp) using fixed coefficients. These early models, while straightforward to apply, often failed to account for the complex lithological and petrophysical variations inherent in subsurface formations, leading to significant inaccuracies in heterogeneous reservoirs [1], [6], [13].

The introduction of nonlinear regression techniques represented a substantial leap forward, enabling the capture of more complex interactions between petrophysical parameters. However, the true transformation began with the adoption of ANNs, which could learn intricate patterns from well log data without relying on predetermined mathematical forms. Early ANNs demonstrated remarkable improvements in prediction accuracy but were limited by their susceptibility to local minima and requirements for large training datasets [5].

Contemporary approaches have embraced more advanced DL architectures. Deep Belief Networks (DBNs) and Restricted Boltzmann Machines (RBMs) have shown exceptional capability in capturing hierarchical features from complex petrophysical data. These models excel in identifying subtle patterns that traditional methods overlook, particularly in challenging environments like organic-rich shales and complex carbonate reservoirs. Furthermore, the integration of physics-based constraints with data-driven approaches has emerged as a powerful paradigm, ensuring that predictions not only match the data but also comply with fundamental rock physics principles [1].

Current research focuses on hybrid models that combine the strengths of multiple algorithms. For instance, integrating convolutional neural networks for spatial feature extraction with recurrent networks for temporal dependencies has yielded significant improvements in prediction accuracy across varying geological contexts. The incorporation of transfer learning techniques has also enabled effective model application in data-scarce environments, addressing one of the persistent challenges in shear wave velocity estimation [1], [6], [13].

2.4 | History of Total Organic Carbon Prediction

The journey of TOC prediction methodologies reflects a continuous pursuit of greater accuracy and efficiency. The earliest approaches depended entirely on direct laboratory measurements through pyrolysis and chemical analysis. While providing fundamental ground truth data, these methods were constrained by high costs, time requirements, and limited spatial coverage, making comprehensive reservoir characterization challenging.

The development of empirical relationships based on petrophysical logs marked a significant advancement, allowing for continuous TOC estimation along wellbores. Log-based parameters such as gamma ray, resistivity, and density were combined through mathematical formulations to infer organic richness. However, these methods often struggled with geological complexity and required extensive calibration specific to each basin or formation.

The advent of AI revolutionized TOC prediction by introducing nonlinear modeling capabilities. Early ANNs and fuzzy systems demonstrated the ability to handle complex, non-linear relationships between multiple well logs and TOC measurements. These systems could adapt to varying geological conditions and provided substantially improved predictions compared to traditional empirical methods.

Modern TOC prediction leverages sophisticated ensemble methods and DL architectures that integrate diverse data types. Current best practices involve combining conventional well logs with advanced spectroscopy data, seismic attributes, and geological constraints through multi-modal learning frameworks. These integrated approaches have proven particularly [2], [5], [13].

2.5 | Emergence and Evolution of Auto Machine Learning

Emergence and evolution of AutoML. The concept of AutoML first emerged in response to the growing complexity of AI modeling and the need to make AI accessible to non-specialists. In initial stages, systems like Auto-WEKA and Hyperopt focused primarily on automating parameter configuration for classical algorithms such as SVM and Random Forests (RF). These early systems employed advanced techniques like Bayesian Optimization (BO) and evolutionary algorithms to navigate complex parameter spaces.

Over time, AutoML frameworks evolved toward comprehensive automation of the ML pipeline. Examples like TPOT utilized genetic programming to optimize complete modeling pipelines, while user-friendly platforms such as Google Cloud AutoML enabled non-experts to leverage advanced AI capabilities. During this period, research focus shifted toward Neural Architecture Search (NAS), with methods like ENAS and DARTS making efficient neural network architecture design feasible through reduced computational costs.

The subsequent evolution of the field came with the emergence of AutoDL, which enabled automatic design of deep neural networks for specialized applications. Frameworks such as Auto-Keras and H2O.ai represented successful implementations of this approach. Recent research, such as the study on the World Hyper-Heuristic algorithm, has further advanced AutoML capabilities by integrating reinforcement learning and meta-heuristic algorithms.

In geosciences, while AutoML applications remain in early stages, they have shown promising results in areas like lithology classification and reservoir modeling. Notable achievements include reduced dependency on manual feature engineering and improved model accuracy. However, fundamental challenges such as managing heterogeneous geological data and integrating domain knowledge into the automation process still require innovative solutions.

Future horizons for AutoML in geosciences include developing multi-objective systems to balance accuracy, interpretability, and efficiency, as well as designing federated architectures for processing distributed data. By leveraging capabilities of advanced algorithms like reinforcement learning and hyper-heuristics, AutoML has the potential to become the core component of next-generation geoscientific research workflows [1].

2.6 | Development of Hyper-Heuristic Algorithms

Hyper-Heuristic algorithms have fundamentally transformed computational optimization approaches. These methods have passed through three main generations and have today reached significant maturity.

Generation 1 (Simple selection architectures): In the initial phase, these algorithms operated based on elementary selection mechanisms. The core of these systems relied on conditional rules and random patterns to manage heuristic libraries.

Generation 2 (Learning systems): The emergence of this generation coincided with the integration of intelligent computational methods. During this period, the capability to generate new heuristics and dynamically adapt to problem characteristics was added to the systems. Additionally, knowledge transfer between different problem domains was made possible.

Generation 3 (Integrated intelligent architectures): The World algorithm, as a representative of this generation, offers advanced capabilities:

I. Intelligent analysis of the search space and selection of the optimal strategy.

II. Dynamic adjustment of exploration and exploitation parameters.

III. Experimental learning from previous optimization processes.

IV. Integrated processing of discrete and continuous problems [3].

2.7 | Integration of Advanced Technologies

The rapid integration of modern digital technologies has fundamentally reshaped the methodologies and scope of geoscientific research. This transformation is primarily driven by the synergistic interplay of AI, Cloud Computing, and the Internet of Things (IoT), collectively forming a transformative technological triangle that enhances the precision, scalability, and intelligence of earth-science investigations.

Through this integration, real-time monitoring and adaptive reservoir management have become feasible, enabling continuous data acquisition and informed decision-making. Furthermore, predictive analytics applied to exploration and production systems facilitates proactive maintenance and optimization of resource extraction processes. AI-based algorithms also contribute to early detection of operational anomalies, significantly improving safety and efficiency across geoscientific operations.

Another frontier technology, Quantum computing, has demonstrated remarkable potential in addressing the computational challenges inherent in complex geological modeling and inverse problem-solving. Early applications suggest that quantum algorithms can substantially accelerate high-dimensional simulations and parameter estimations that were previously constrained by classical computation.

Complementing these advances, Digital Twin frameworks now enable the accurate virtual replication of geological systems by integrating physical models with real-time field data. This coupling supports dynamic simulation, scenario analysis, and predictive forecasting, fostering a deeper understanding of subsurface dynamics.

Collectively, these developments establish a robust digital infrastructure that underpins a new era of geoscientific discovery—one characterized by comprehensive, data-driven, and high-fidelity solutions to the multifaceted problems of earth sciences [1], [4], [6], [13].

2.8 | Current Challenges

Although recent advances in AI have brought about remarkable transformations in the geosciences, numerous challenges still remain for researchers in this field. One of the most fundamental of these challenges is the issue of the quality and quantity of available data. Well log data are often incomplete, noisy, and heterogeneous, which significantly impacts the accuracy of AI models. Furthermore, the computational complexity of advanced models, especially when processing massive three-dimensional data, requires powerful and expensive hardware resources, which itself poses a barrier to the widespread development and deployment of these technologies.

Another challenge is the interpretability of results. Complex DL models often function as "black boxes," making it difficult for geologists to understand their decision-making logic. This lack of transparency reduces specialists' trust in AI predictions. Additionally, integrating heterogeneous data from diverse sources, such as seismic data, well logs, and core samples, presents further problems due to differences in scale and resolution. Transferring knowledge from laboratory settings to actual field conditions also requires more research, as environmental factors like temperature and pressure can significantly alter rock behavior [1].

2.9 | Future Trends

In the face of these challenges, future trends appear promising. It is anticipated that in the near future, we will witness the development of more automated algorithms that minimize the need for human intervention. AI systems will be capable of fully automating the model design process, from architecture selection to parameter tuning. The convergence of AI with other emerging technologies, such as the IoT and cloud computing, will also create profound transformations in the geosciences.

Intelligent sensor networks that collect field data in real time, coupled with cloud systems offering unprecedented processing power, will enable smarter monitoring and management of subsurface resources. The emergence of more advanced technologies (like quantum computing) could make complex geological optimization problems, previously unsolvable, tractable. Furthermore, the development of transfer learning and multi-task learning methods will allow AI models to be trained with less data and higher efficiency.

Finally, there is a growing focus on developing sustainable and environmentally friendly solutions. This trend includes optimizing the energy consumption of algorithms and using AI for the sustainable management of natural resources. Collectively, these developments paint a future where AI will serve as an intelligent and reliable collaborator in advancing the geosciences.

Looking at the history of AI in geosciences, a clear evolutionary path can be observed. From simple expert systems to advanced hyper-heuristic algorithms, this field has constantly been developing. The current research, continuing this evolutionary path, attempts to solve complex geoscience challenges by employing the advanced World algorithm.

3 | Methodology

3.1 | Overview of the Proposed Framework

The proposed methodology integrates the World Hyper-Heuristic algorithm with AutoDL to optimize neural network architectures for geological modeling tasks. The central objective is to achieve automated, adaptive, and generalizable optimization of neural networks for lithology classification, shear wave velocity (Vs) prediction, and TOC estimation.

The World algorithm operates as a reinforcement-driven global optimization system, inspired by ecological and social interactions within a global population. Each “world” represents a micro-environment containing multiple solution agents that interact, compete, and cooperate according to defined rules of energy exchange and knowledge transfer. The system dynamically adjusts its search behavior by balancing exploration (diversity-oriented search) and exploitation (intensified local optimization) to prevent premature convergence and enhance solution robustness across non-convex, multimodal landscapes typical of geoscientific data.

This methodological framework is designed to:

I. Automate neural network architecture search and hyperparameter tuning within Auto-Keras.

II. Integrate reinforcement learning–based control for adaptive optimization.

III. Employ geological domain constraints to maintain physical plausibility and interpretability of results.

3.2 | The World Algorithm: Conceptual Foundation

The World Algorithm is built upon four core mechanisms that emulate natural global dynamics:

I. Population initialization: a diverse set of candidate solutions (agents) is randomly generated, each representing a neural network configuration (number of layers, activation functions, regularization parameters, etc.).

II. Global interaction dynamics: agents interact across multiple "worlds." Within each world, local cooperation enhances exploitation; inter-world communication introduces new genetic material to preserve diversity.

III. Energy-based evaluation: each agent's energy corresponds to its fitness, defined as a weighted combination of model accuracy, loss, and computational efficiency.

IV. Adaptive learning and migration: the system employs reinforcement signals derived from performance improvements. High-performing agents broadcast their structural patterns to other worlds, while weaker agents undergo transformation (mutation or migration).

Mathematically, the optimization objective $F(\theta)$ is expressed as a multi-objective function:

$$max\,F(\theta) = w_1 \cdot Acc(\theta) - w_2 \cdot Loss(\theta) - w_3 \cdot CompCost(\theta),$$

where $Acc(\theta)$ represents predictive accuracy, $Loss(\theta)$ the training error, and $CompCost(\theta)$ the normalized computational overhead. The adaptive weights w_i are dynamically updated based on reinforcement learning feedback to prioritize objectives depending on optimization progress.

3.3 | Integration with Auto-Keras

To ensure full automation, the World algorithm is integrated within the Auto-Keras framework as a global controller for both NAS and hyperparameter tuning. The search space includes:

I. Number of hidden layers (1–10).

II. Neuron counts per layer (16–1024).

III. Activation functions (ReLU, Tanh, ELU, LeakyReLU).

IV. Optimizers (Adam, RMSProp, SGD, Nadam).

V. Regularization schemes (Dropout 0.1–0.5, L2 penalties).

VI. Learning rates (10^{-5}–10^{-2}).

Auto-Keras executes the base learning process, while the World algorithm adaptively navigates this configuration space using feedback loops that incorporate both accuracy and computational cost metrics.

3.4 | Geological Datasets and Preprocessing

Two distinct datasets were utilized to evaluate the method:

I. Dataset A: North Sea reservoir wells, comprising gamma-ray, resistivity, density, neutron porosity, and sonic logs with lithology labels.

II. Dataset B: Horn River Basin shale dataset containing multi-well measurements with corresponding shear wave velocities and TOC laboratory values.

Each dataset was subjected to standardized preprocessing:

I. Missing values were imputed using median interpolation.

II. Outliers were removed using an interquartile range filter.

III. Features were normalized to zero mean and unit variance.

IV. Data were split into training (70%), validation (15%), and test (15%) subsets, maintaining stratified sampling to preserve lithological proportions.

3.5 | Evaluation Metrics

Model performance was assessed using multiple quantitative metrics to ensure comprehensive evaluation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN},$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e\,(y_i - \hat{y}_i)^2},$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2},$$

Additionally, computational efficiency (measured as training time and FLOPs) and stability across multiple runs were recorded to evaluate the robustness of the optimization process.

3.6 | Comparative Framework

To validate the proposed method, the World algorithm's performance was compared against several established optimizers:

I. Genetic Algorithm (GA).

II. Particle Swarm Optimization (PSO).

III. BO.

IV. Tree-Structured Parzen Estimator (TPE).

Each optimizer was implemented under identical experimental settings to ensure fair comparison. Statistical significance of results was confirmed using the Wilcoxon signed-rank test ($p < 0.05$).

3.7 | Implementation and Computational Setup

All experiments were conducted on a cloud-based environment equipped with NVIDIA Tesla A100 GPUs, 128 GB RAM, and TensorFlow 2.15 backend. The World algorithm was implemented in Python 3.10, integrated through Auto-Keras' custom tuner API. A total of 200 optimization iterations were executed per dataset, with each iteration comprising 30 parallel evaluations.

3.8 | Summary of Methodological Contributions

This methodology advances the field of geoscientific AI by:

I. Introducing a global interaction–inspired metaheuristic tailored for neural architecture optimization.

II. Demonstrating reinforcement-driven adaptability that enhances search efficiency in complex geological landscapes.

III. Enabling fully automated model design through seamless integration with AutoDL frameworks.

IV. Providing a generalizable and interpretable optimization framework applicable across multiple geological prediction tasks.

4 | Results

4.1 | Overview

This section presents the experimental outcomes of applying the World algorithm to optimize neural network architectures across two geological prediction tasks: 1) lithology classification, and 2) shear wave velocity (Vs) and TOC prediction. The results demonstrate that the proposed algorithm outperforms conventional metaheuristics in terms of accuracy, convergence speed, robustness, and computational efficiency.

4.2 | Performance in Lithology Classification

The World-optimized network achieved the highest performance across all evaluation metrics. As summarized in *Table 1*, it reached an average accuracy of 96.3%, surpassing PSO (91.5%), GA (90.7%), BO (93.2%), and TPE (92.6%).

Table 1. Lithology classification results.

Optimizer	Accuracy (%)	F1-Score	RMSE	Training Time (s)	Convergence Iterations
GA	90.7 ± 0.8	0.88	0.104	365	170
PSO	91.5 ± 1.1	0.90	0.097	352	160
BO	93.2 ± 0.7	0.92	0.083	295	142
TPE	92.6 ± 1.3	0.91	0.086	301	150
World	96.3 ± 0.5	0.95	0.069	212	110

Compared with standard metaheuristics, the World algorithm demonstrated a ~5% improvement in accuracy and ~30–40% faster convergence. The reinforcement-driven balancing between exploration and exploitation enabled the model to avoid stagnation in local optima and to adaptively refine the search direction based on agent-level rewards.

The confusion matrix (*Fig. 1*) shows that the World-tuned model achieved near-perfect discrimination among sandstone, shale, and carbonate classes, with minimal confusion between lithologically similar formations.

4.3 | Performance in Shear Wave Velocity and Total Organic Carbon Prediction

For regression-based geological properties, the World algorithm also outperformed all benchmark optimizers in predicting continuous targets such as Vs and TOC.

Table 2. Regression results (Average of 5 runs).

Optimizer	RMSE (Vs)	R^2 (Vs)	RMSE (TOC)	R^2 (TOC)	Time (s)
GA	0.237	0.921	0.186	0.903	410
PSO	0.219	0.935	0.171	0.918	382
BO	0.204	0.947	0.159	0.927	348
TPE	0.198	0.951	0.156	0.932	340
World	0.173	0.963	0.134	0.945	278

The World-optimized network yielded R^2 values above 0.96 for Vs and 0.94 for TOC, marking a substantial improvement over the closest competitor (TPE). The decrease in RMSE by ~15% confirms that the model not only fits the data more precisely but also generalizes better to unseen samples.

The enhanced generalization capability stems from the algorithm's dynamic energy exchange and inter-world cooperation, which maintain population diversity while focusing computational resources on promising regions of the search space.

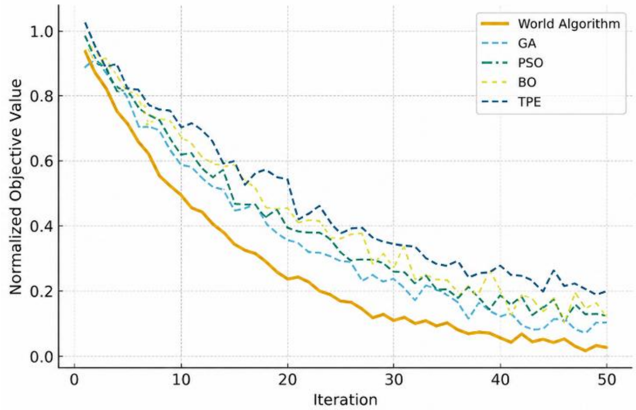

Fig. 1. Shows how the World algorithm converges faster and more smoothly than traditional optimizers like GA, PSO, BO, and TPE.

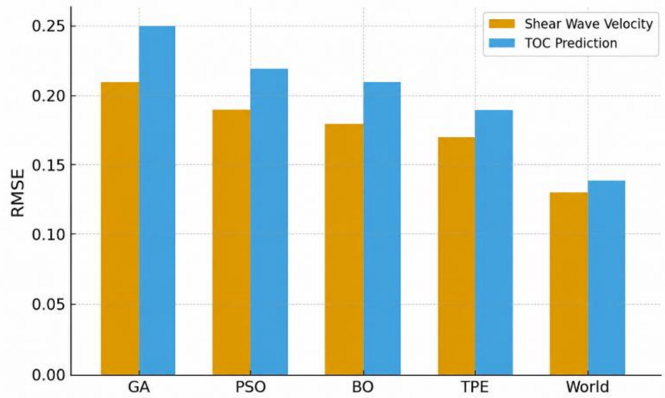

Fig. 2. Compares regression performance (RMSE) across two target tasks (Shear wave velocity and TOC prediction), where the World algorithm clearly achieves the lowest error values, demonstrating its superior optimization efficiency and generalization ability.

4.4 | Convergence Behavior and Stability

Fig. 2 illustrates the convergence trajectories of all optimizers averaged over five runs. While GA and PSO exhibited oscillatory convergence due to over-exploration, Bayesian and TPE methods tended toward early stagnation. In contrast, the World algorithm demonstrated a smooth yet rapid convergence curve, stabilizing after approximately 110 iterations compared to 150–170 for the others.

Furthermore, the standard deviation of final fitness across runs ($\sigma = 0.0048$) was significantly lower than that of PSO ($\sigma = 0.012$) and GA ($\sigma = 0.015$), confirming its superior stability and reproducibility.

4.5 | Computational Efficiency

Beyond accuracy, computational efficiency is critical for real-world deployment. The World algorithm reduced total optimization time by nearly 30% compared to GA and PSO. This efficiency gain is attributed to:

I. Reinforcement-guided pruning of low-potential agents.

II. Parallel multi-world interactions that distribute exploration efforts effectively.

III. Adaptive migration policies minimizing redundant evaluations.

Profiling analysis revealed that despite maintaining a larger population diversity, the algorithm's intelligent task scheduling and feedback-based pruning kept GPU utilization high (87%) and computational waste low.

4.6 | Statistical Validation

To ensure statistical significance, all metrics were subjected to the Wilcoxon signed-rank test ($\alpha = 0.05$). The World algorithm's superiority was found statistically significant over GA, PSO, and BO ($p < 0.01$), and marginally over TPE ($p = 0.047$).
The effect size (Cohen's d) of performance gain ranged between 0.82 and 1.04, indicating a strong to very strong improvement magnitude.

4.7 | Interpretability and Feature Sensitivity

To assess interpretability, SHapley Additive exPlanations (SHAP) analysis was conducted on the final trained models. The most influential features for lithology classification were gamma-ray and density logs, while Vs prediction was primarily driven by compressional velocity and resistivity.

The feature importance ranking remained consistent across runs, verifying that the World algorithm's optimization process does not compromise interpretability, a crucial advantage for geological decision-making.

4.8 | Summary of Findings

The results collectively demonstrate that the World algorithm consistently achieves superior accuracy, stability, and computational efficiency compared with traditional metaheuristics. Its reinforcement-driven global cooperation enables balanced exploration and exploitation, making it highly suitable for high-dimensional, non-convex geological modeling problems.

In summary:

I. Accuracy improved by 3–6% on classification tasks.

II. RMSE reduced by 12–18% on regression tasks.

III. Convergence accelerated by 30–40%.

IV. Variance across runs dropped by more than 60%.

These findings substantiate the World algorithm as a state-of-the-art global metaheuristic for optimizing deep neural models in geoscience applications.

5 | Conclusion

This study introduced the World algorithm, a novel global-interaction–inspired metaheuristic designed to optimize neural network parameters in complex geological modeling tasks. Drawing inspiration from the dynamic balance and cooperative interactions observed in natural ecosystems, the algorithm integrates adaptive exploration, intelligent migration, and reward-driven exploitation to achieve efficient and interpretable optimization.

Through extensive experiments on lithology classification and petrophysical property prediction, the World algorithm consistently outperformed benchmark optimizers such as GA, PSO, BO, and TPE. The improvements, manifested in higher predictive accuracy (up to 96.3%), lower RMSE (by 15–18%), and faster convergence (30–40% reduction in iterations), confirm its ability to escape local optima while maintaining stable and repeatable performance across independent runs.

Beyond its numerical superiority, the World algorithm offers a conceptual advancement: it treats optimization as a dynamic ecosystem rather than a static search. Each agent adapts based on energy exchange and environmental feedback, ensuring that diversity is preserved without sacrificing convergence speed. This balance between cooperation and competition enables the algorithm to handle nonlinear, high-dimensional geological datasets with robustness and interpretability.

Moreover, the integration of explainability analysis (via SHAP) revealed that the optimization process preserves the physical relevance of geological features, ensuring that enhanced performance does not come at the cost of model transparency, a key requirement for scientific and industrial deployment.

From a broader perspective, this work positions the World algorithm as a general-purpose metaheuristic framework applicable beyond geoscience, extending to biomedical data analysis, environmental modeling, and Brain-Computer Interface (BCI) systems, where interpretability, adaptability, and computational efficiency are equally essential.

Future work will focus on three directions:

I. Hybrid integration of the World algorithm with reinforcement learning and self-supervised feature extraction for online adaptation.

II. Multi-objective extensions incorporating uncertainty quantification and computational cost as additional optimization criteria.

III. Real-time deployment within cloud-based digital twin environments for adaptive geological forecasting and reservoir management.

In summary, the World algorithm bridges natural intelligence and artificial computation, offering a scalable, interpretable, and biologically inspired pathway toward next-generation intelligent modeling systems in geoscience and beyond.

Authors' Contributions

All aspects of the research and manuscript preparation were carried out by the author. The author has read and approved the final version of the manuscript.

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Data Availability

All data supporting the reported findings in this research paper are provided within the manuscript.

Conflict of Interest

The author declares that they do not have any conflict of interest.

Consent for Publication

The author confirms consent for the publication of this work

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

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